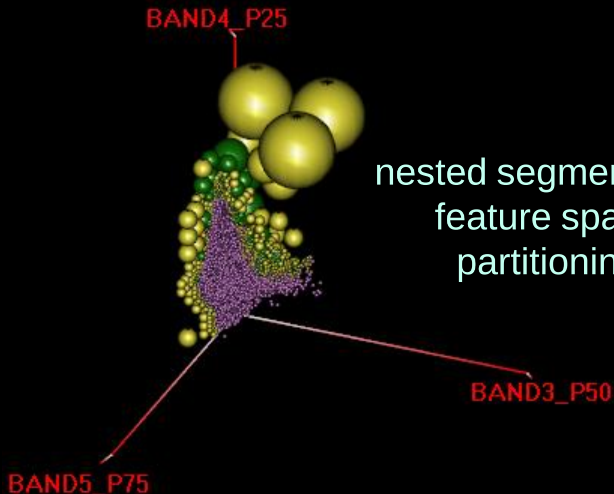
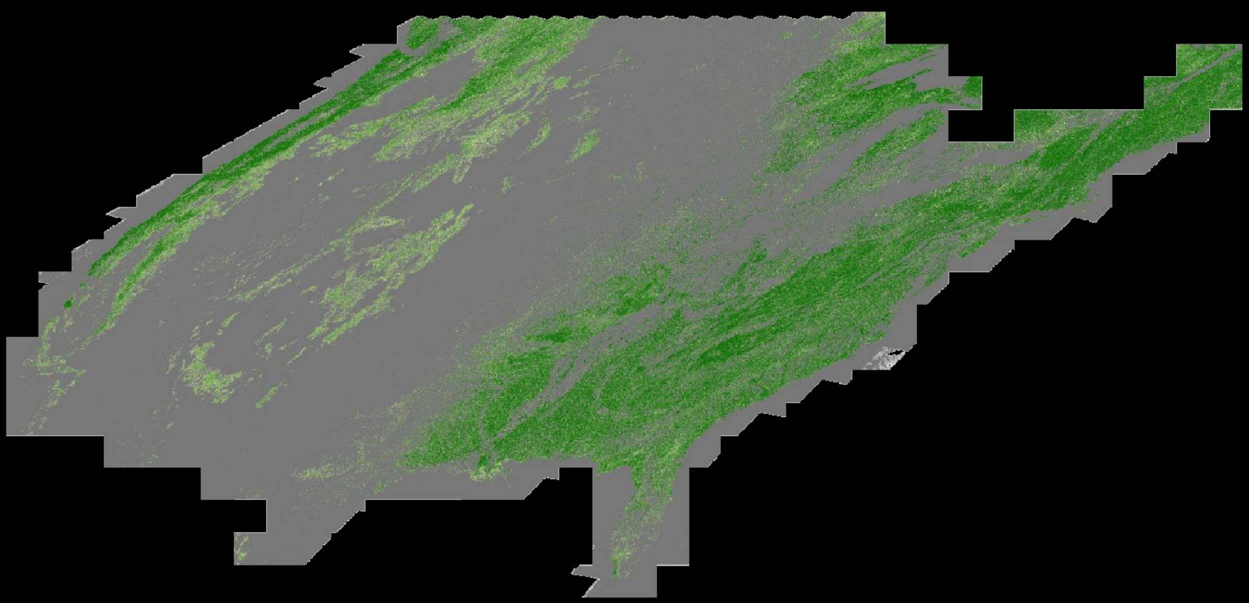
The use of nested segmentation active-learning for large area Landsat classification

Alexey Egorov, David Roy & Matt Hansen
SDSU GSCE & University Maryland



nested segmentation feature space partitioning

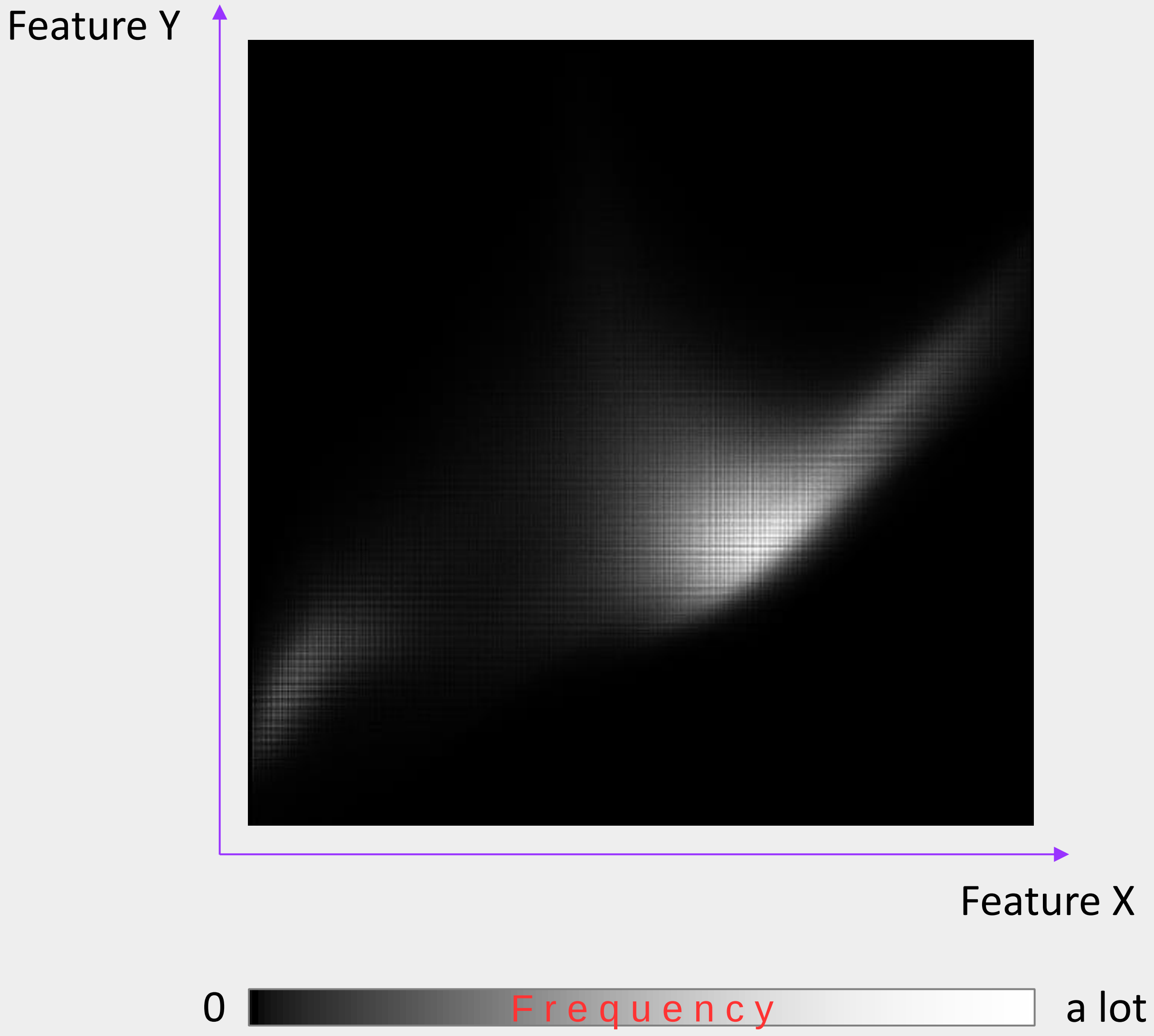
% tree cover map



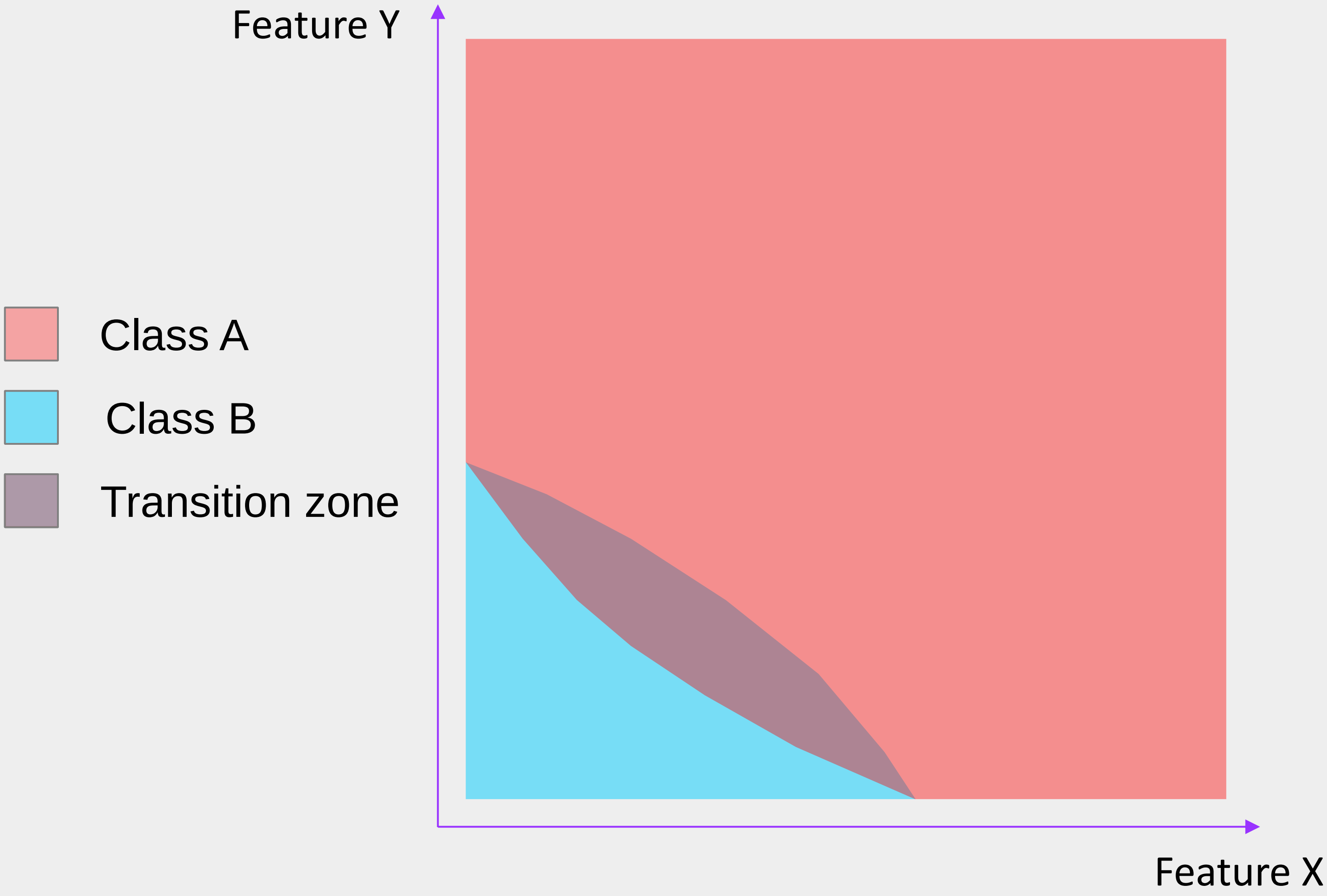
Training data collection

Targeted sample vs Random sample

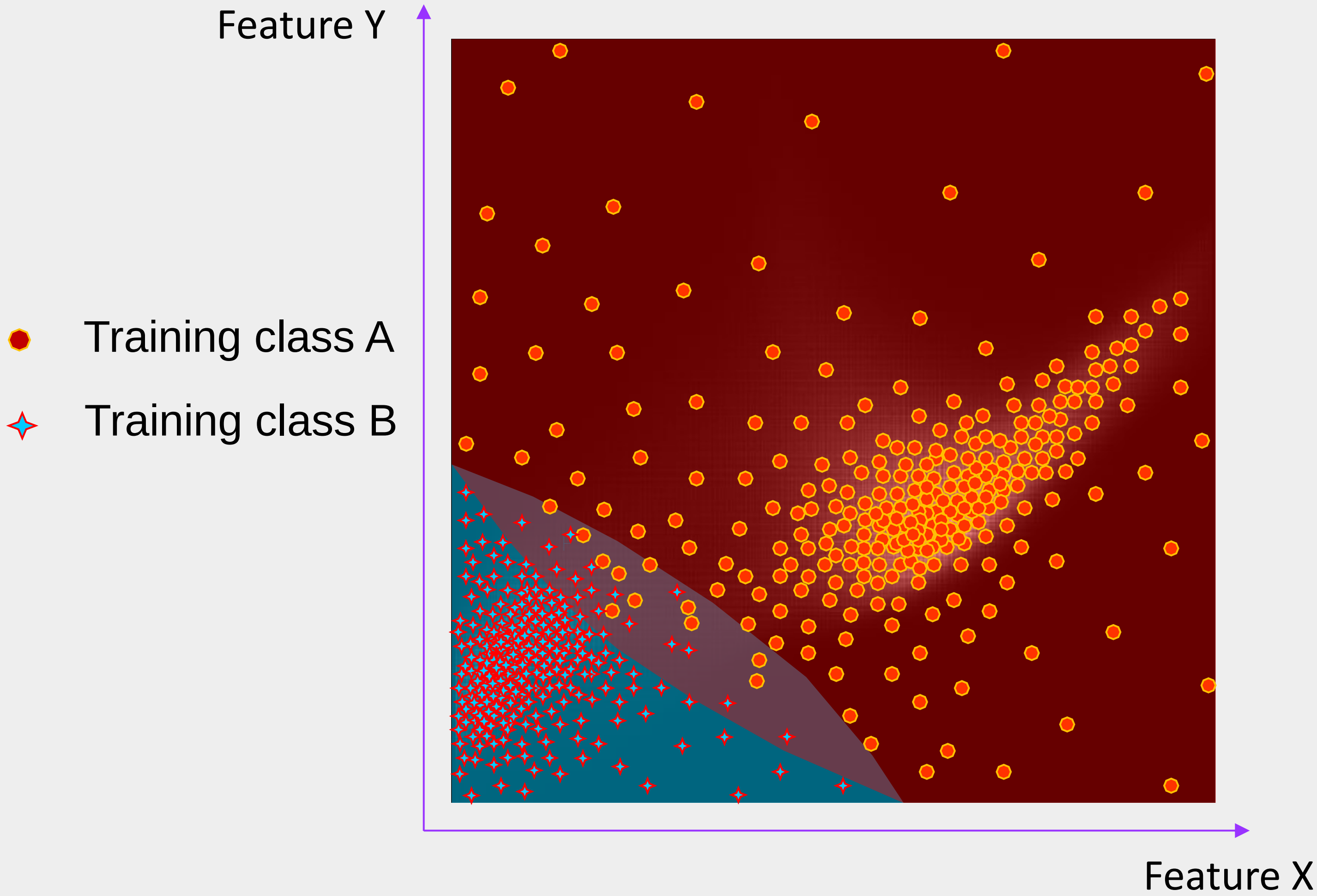
Feature space cartoon



Two hypothetical classes distribution in feature space

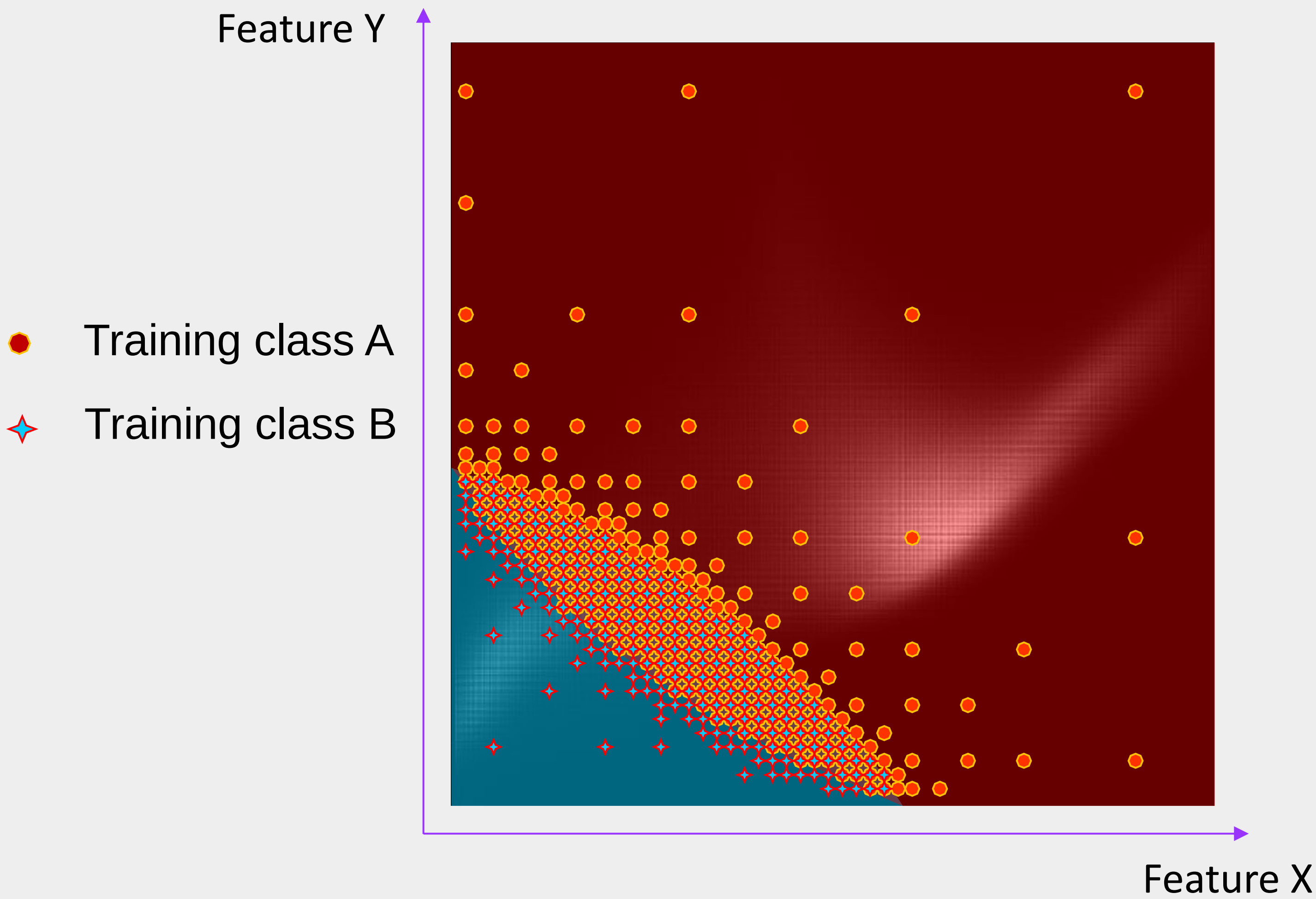


Training data random sample



Random sample proportional to class A and B distribution in feature space

Training data targeted sample



Targeted sample to more precisely separate class A and B

Active learning

&

Nested Segmentation feature space partitioning

Egorov, Hansen, Roy, Kommareddy, Potapov, 2015,
Image interpretation-guided supervised classification using nested segmentation, *Remote Sensing of Environment,* 165, 135–147.

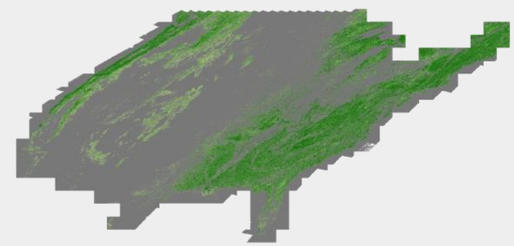
Active learning concepts

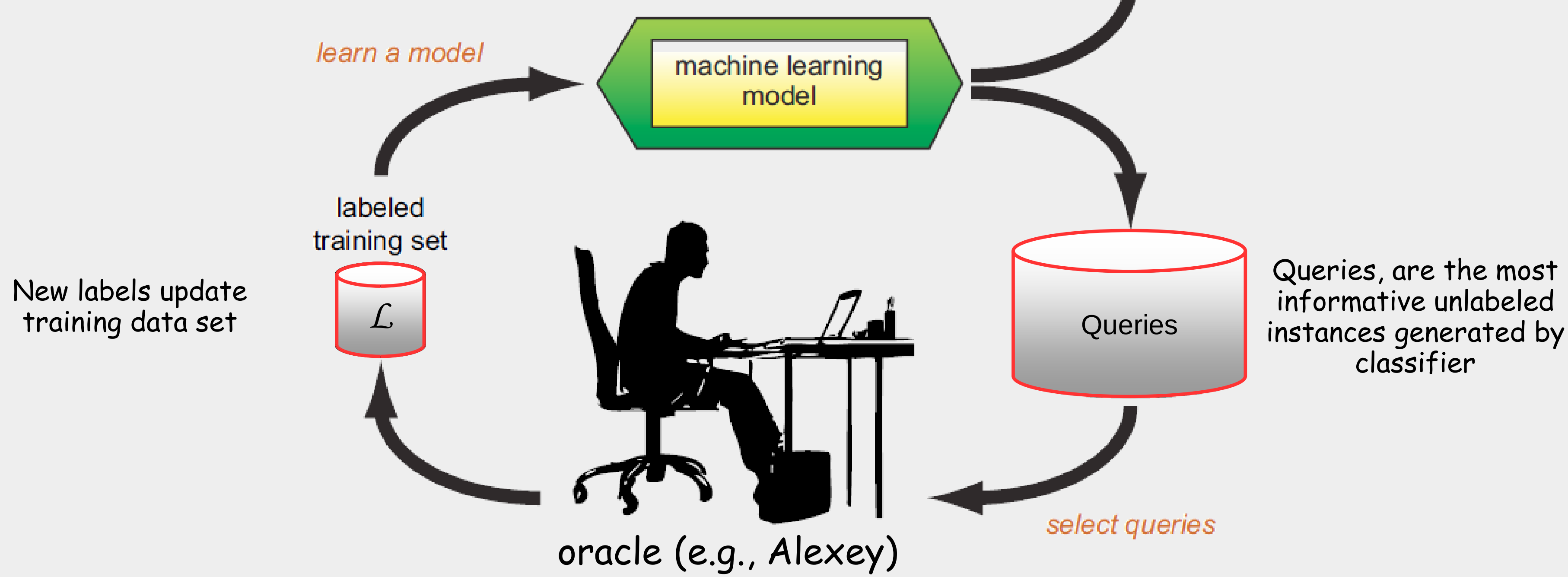
Overcome class labeling bottlenecks by asking queries in the form of unlabeled instances to be labeled by an oracle (e.g., a human annotator)

Goals:

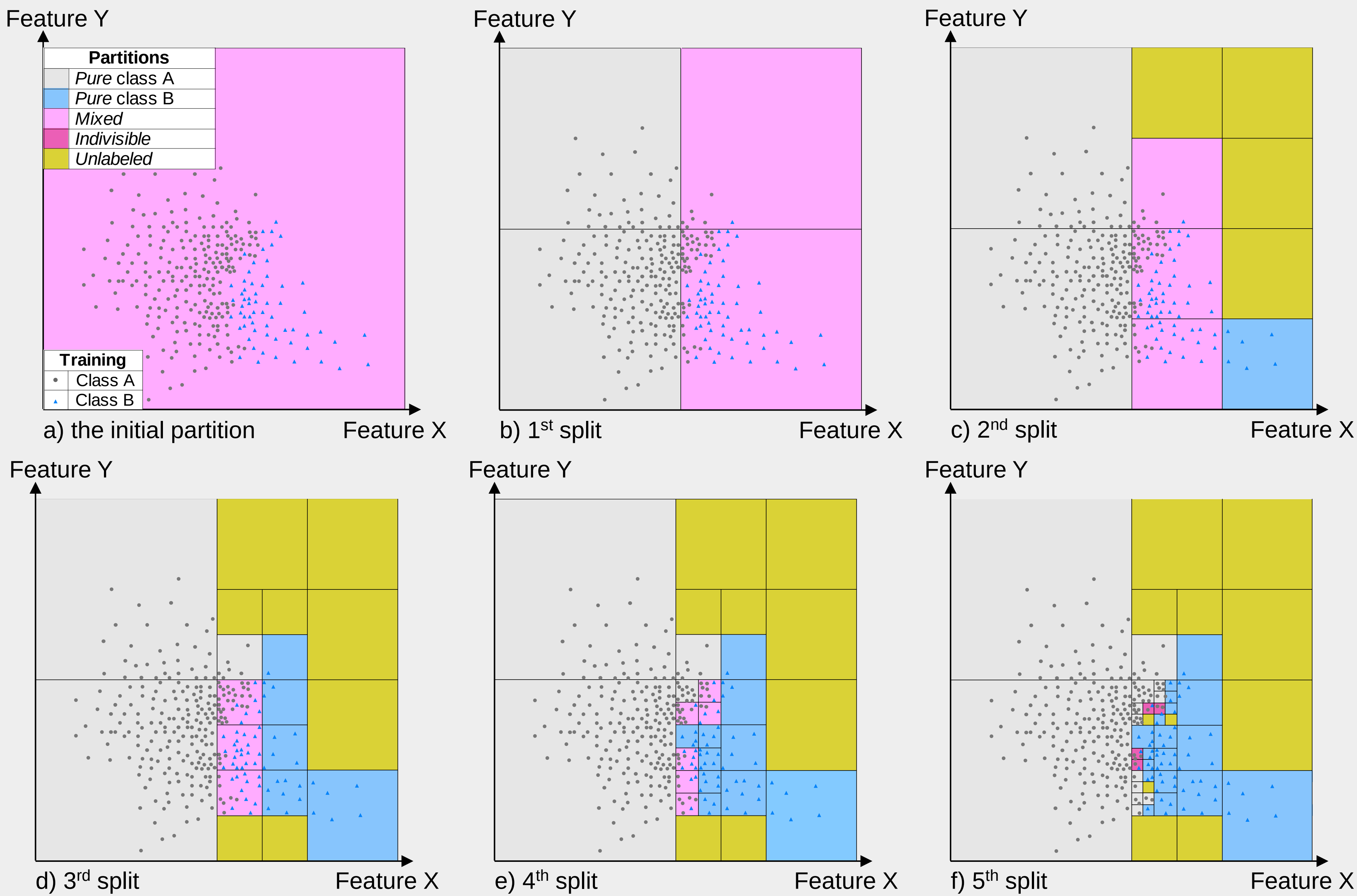
- achieve high classification accuracy using as few labeled instances as possible
- minimize cost of obtaining labeled data
- reduce computational complexity

Each iteration refines model and improves the classification accuracy





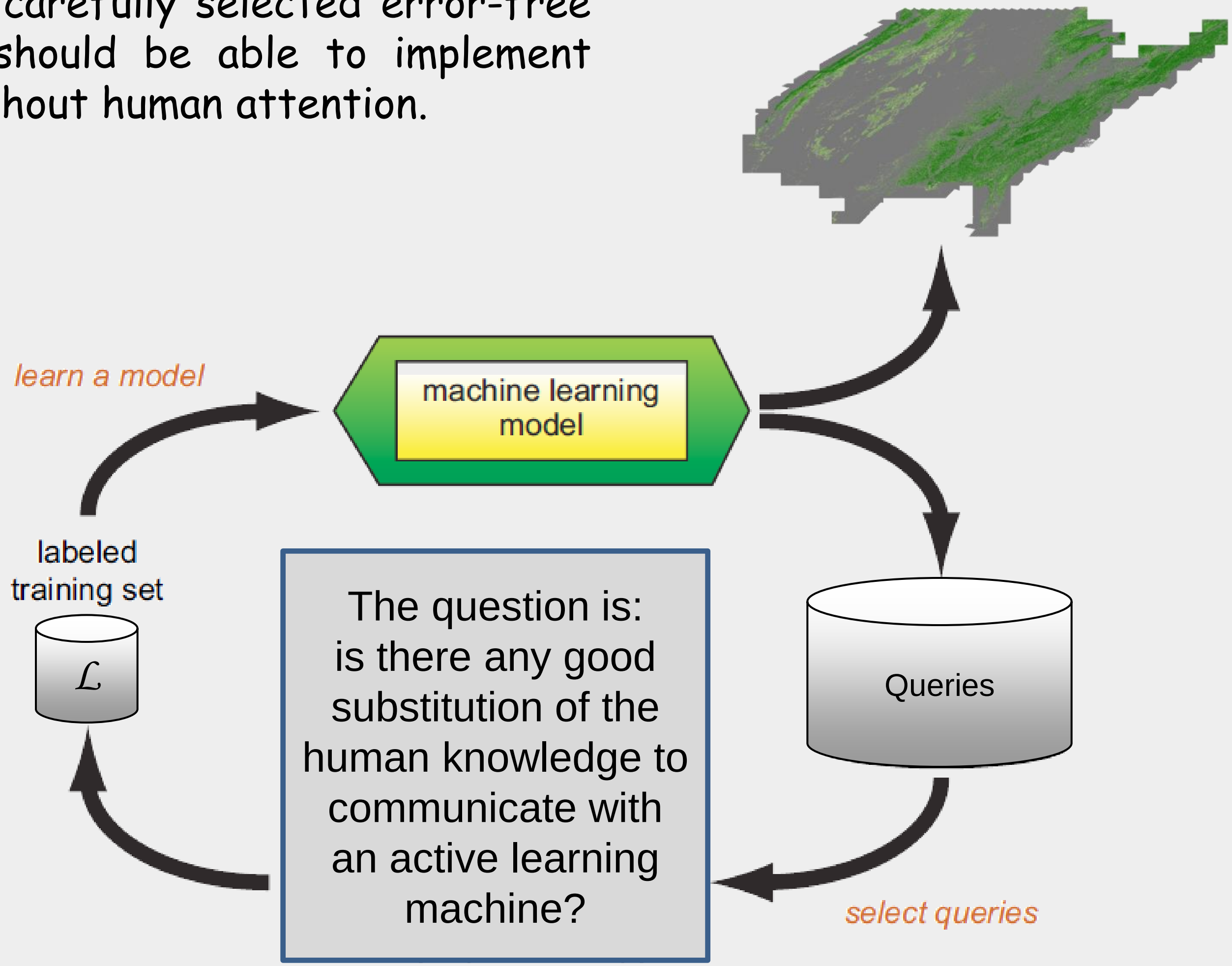
Nested Segmentation feature space partitioning



Active learning – replace the human

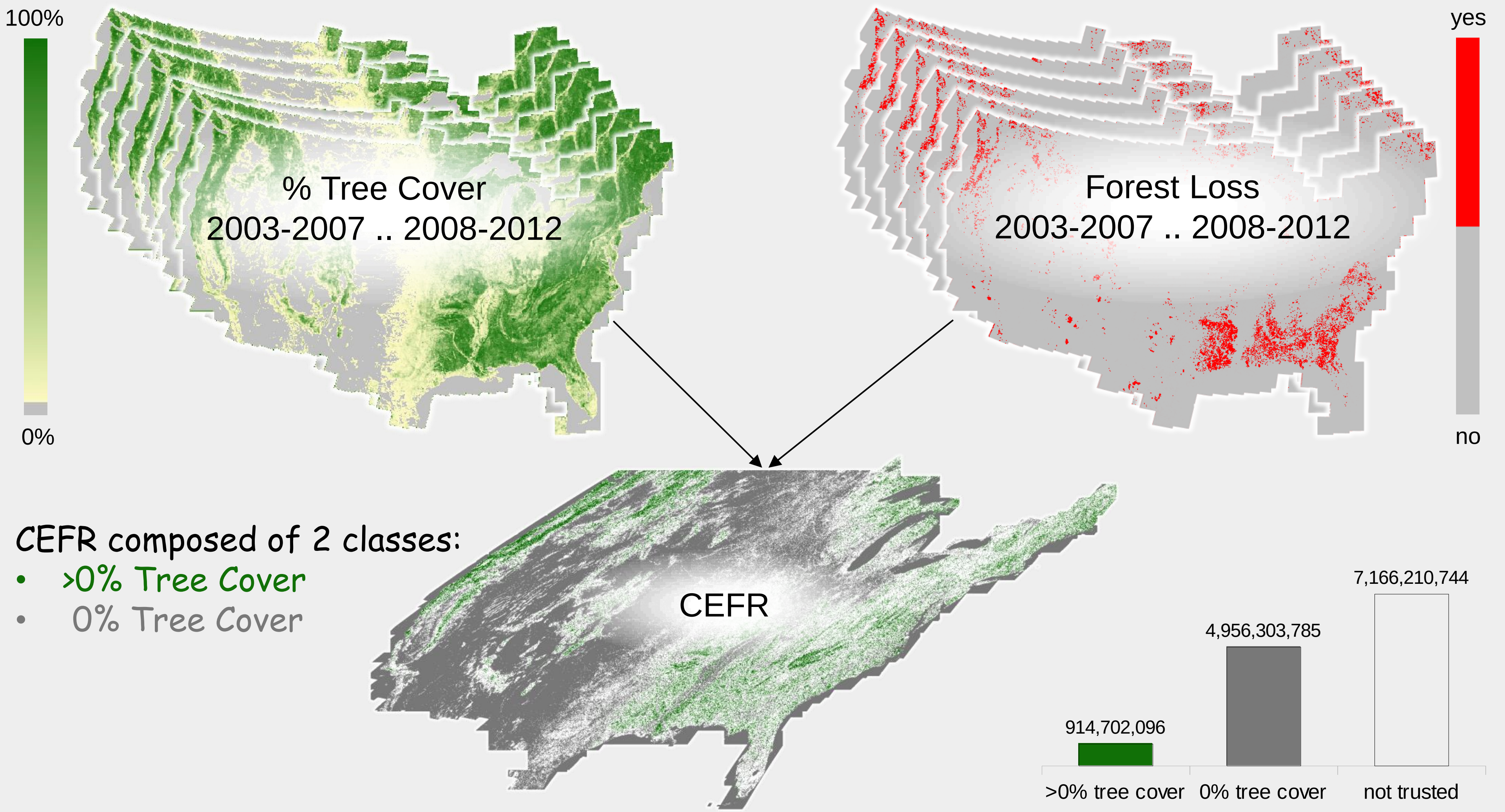
A human annotator is not the only source of training labels.

With a large but carefully selected error-free reference data, should be able to implement active learning without human attention.



2-class commission error-free reference (CEFR) generation

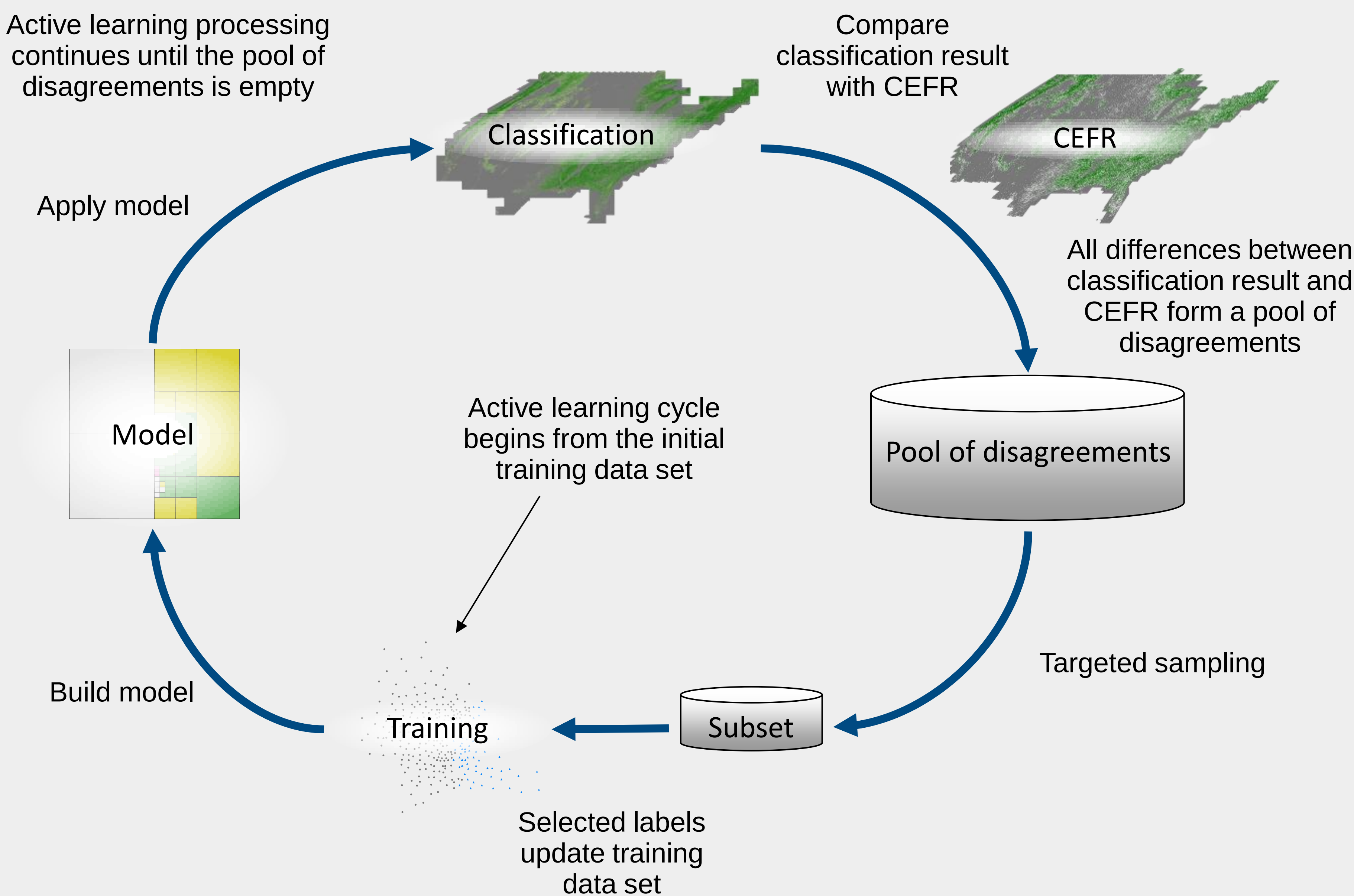
Use 5-year WELD generated 30m % tree cover and binary forest loss products for six epochs (2003-2007, 2004-2009, …, 2008-2012) (Hansen et al., 2011, 2014)



>0% Tree Cover when all 6 epochs classified as (>0% Tree Cover AND no forest loss)

0% Tree Cover when all 6 epochs classified as (0% Tree Cover AND no forest loss)

Active learning cycle

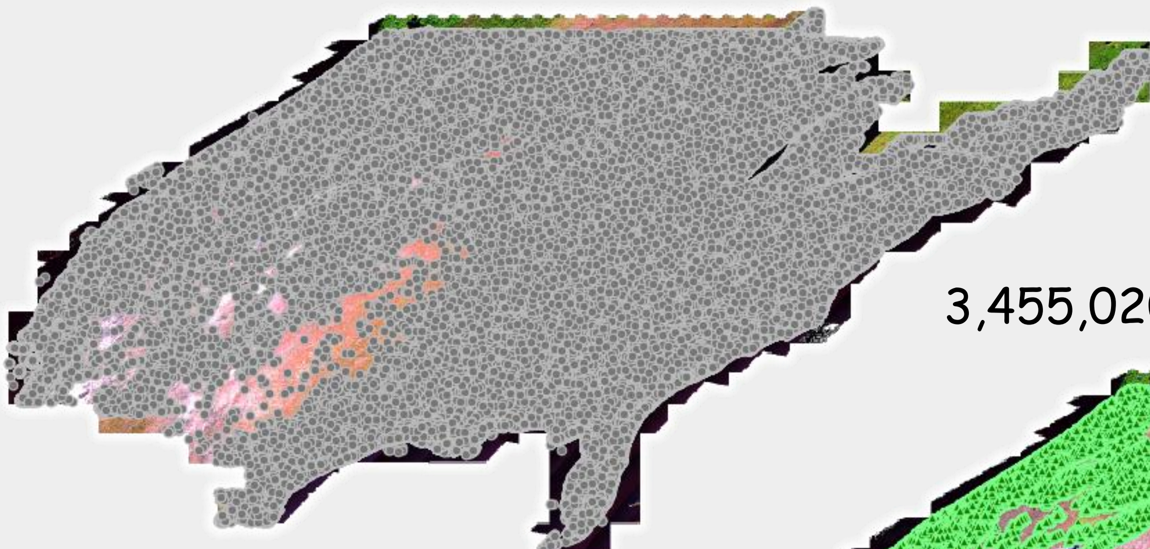


Targeted sampling

Initialized with a few >0% Tree Cover and 0% Tree Cover pixels from CEFR (composed of 915 million >0% Tree Cover and 4,956 million 0% Tree Cover pixels).

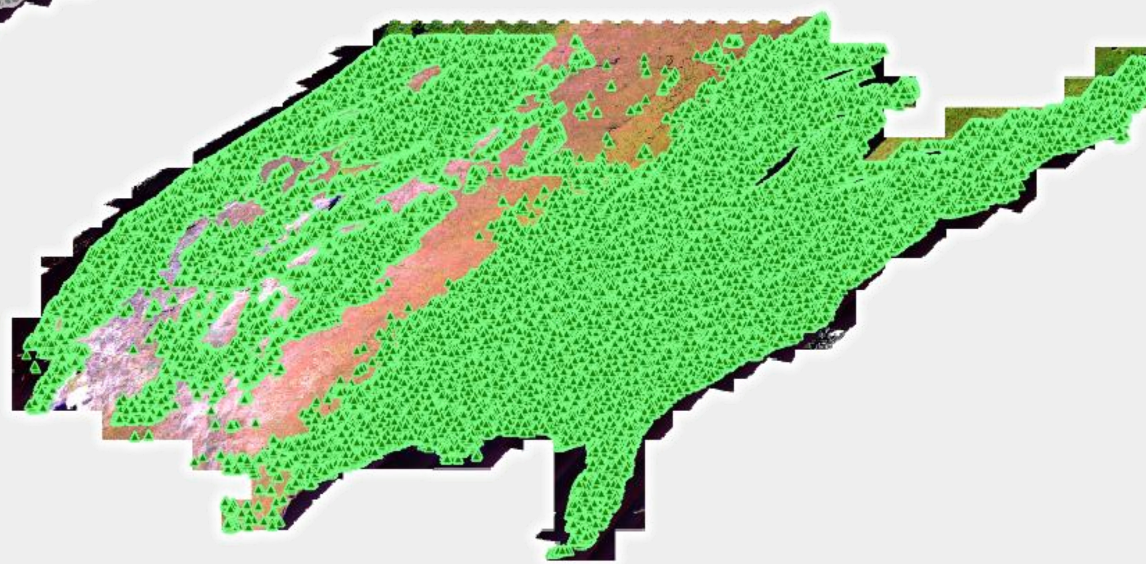
After 120 cycles the active learning machine collected:

3,127,427 0% Tree Cover training pixels



0.1% sampling rate

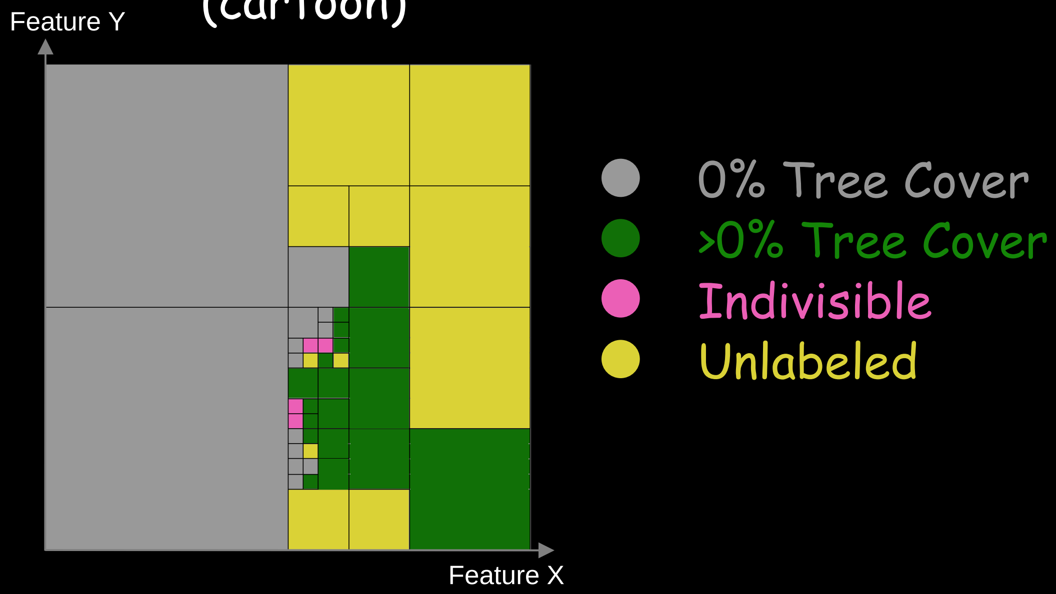
3,455,020 >0% Tree Cover training pixels



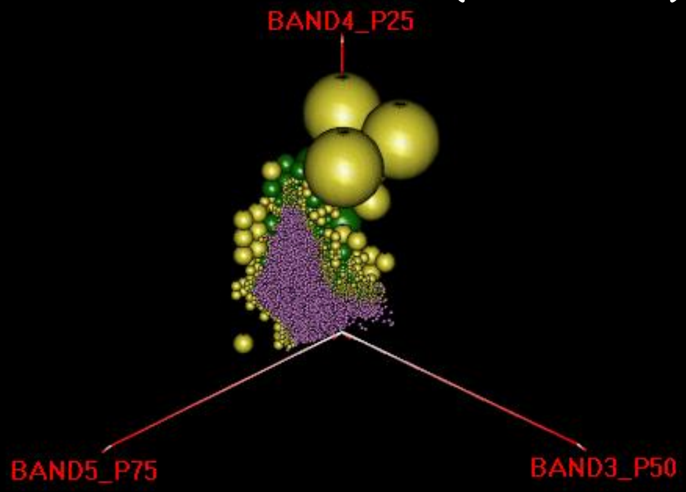
Building a classification model

3,455,020 >0% Tree Cover and 3,127,427 0% Tree Cover pixels provide a parsimonious Nested Segmentation feature space partitioning.

2D toy example (cartoon)



Tree cover classification model in first 3 dimensions (real data)

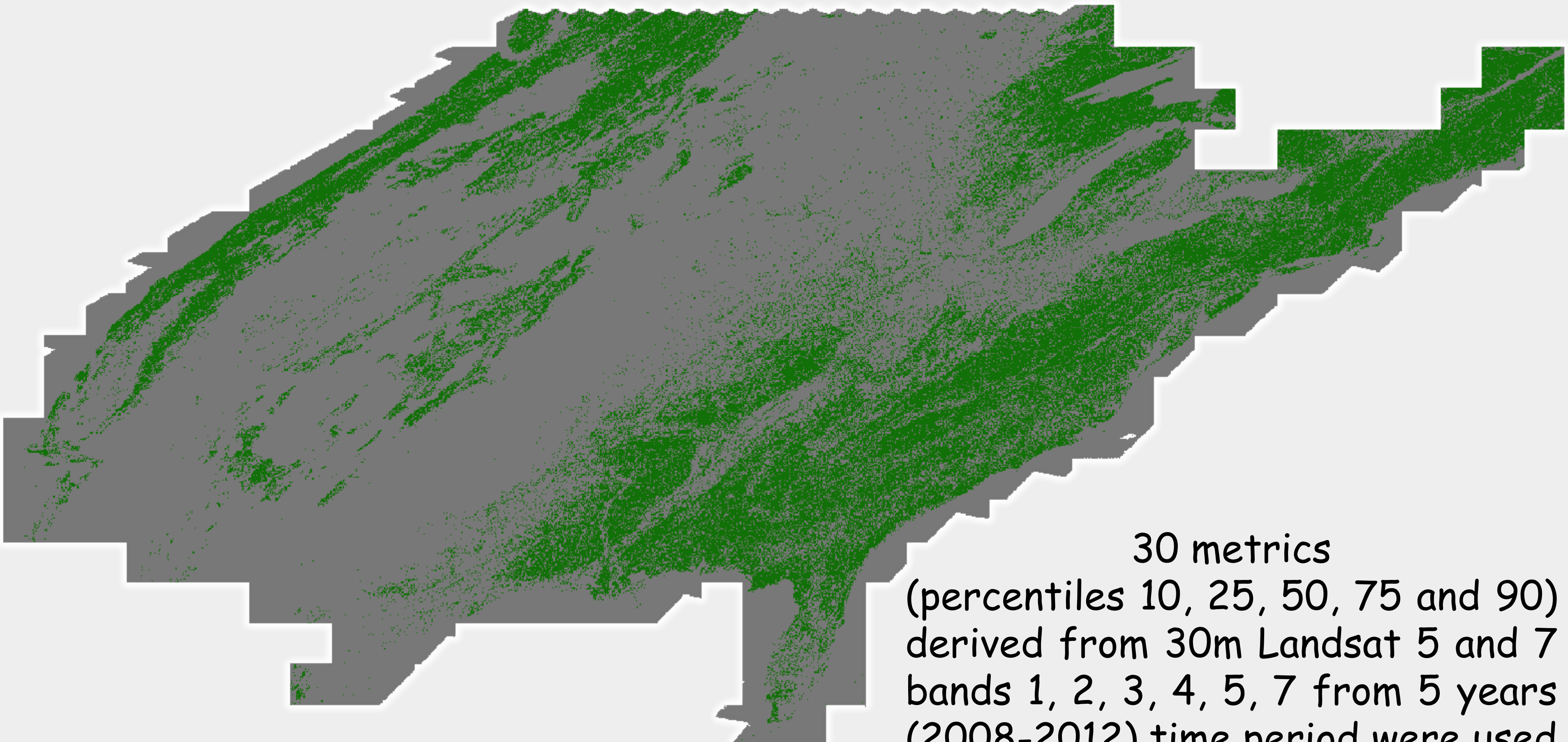


Partitions are shown as spheres for better 3D visualization, though in fact all partitions are boxes (cubes in 3D). 0% Tree Cover partitions are omitted in 3D.

30 metrics (percentiles 10, 25, 50, 75 and 90) derived from 30m Landsat 5 and 7 bands 1, 2, 3, 4, 5, 7 for 5 years (2008-2012) were used as explanatory variables.

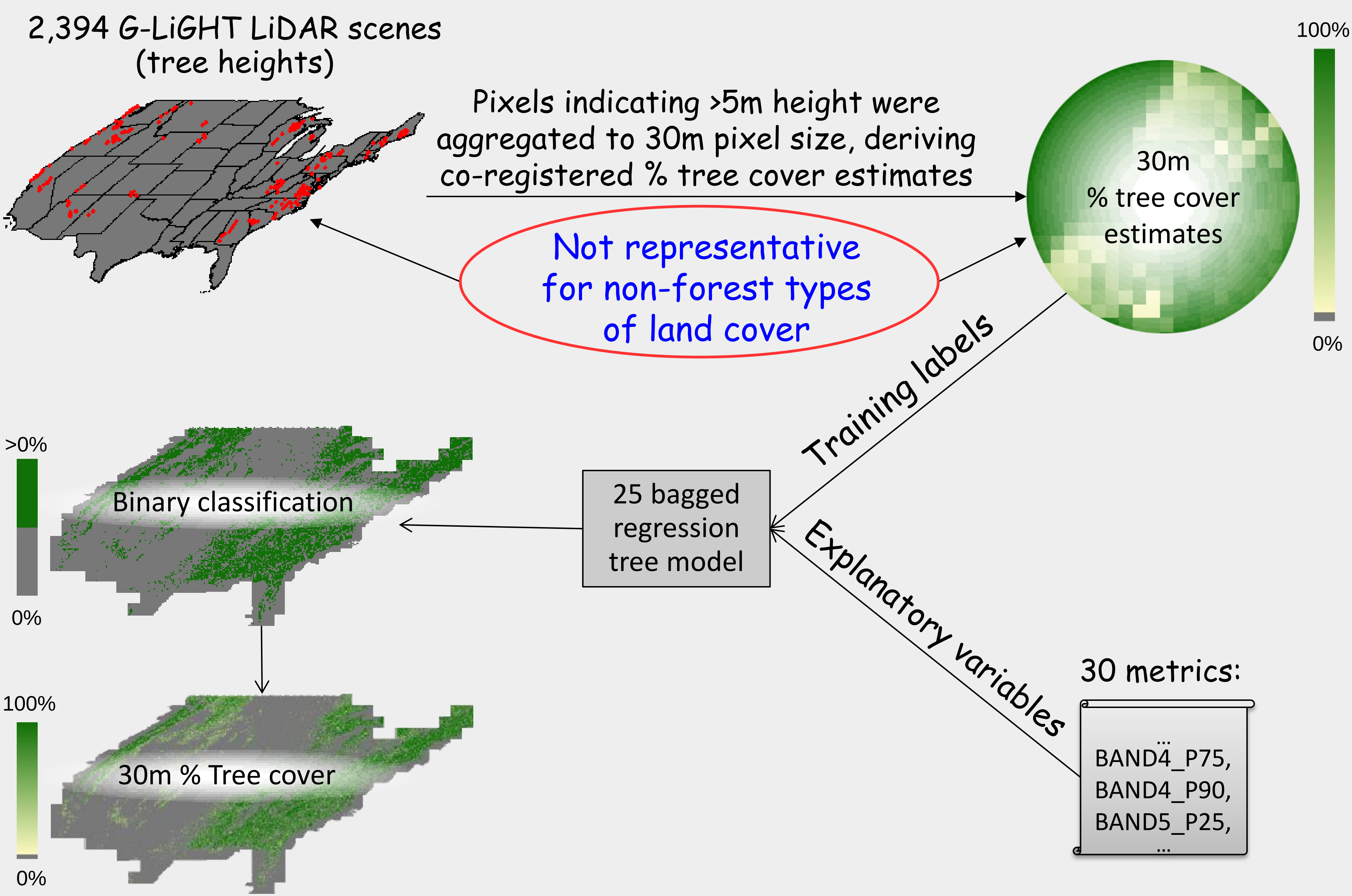
Binary (2-class) classification

With the 3,455,020 <0% Tree Cover and 3,127,427 0% Tree Cover training pixels provide a parsimonious Nested Segmentation feature space partitioning and applied to all 30m CONUS pixels to generate a binary (tree/no tree) map

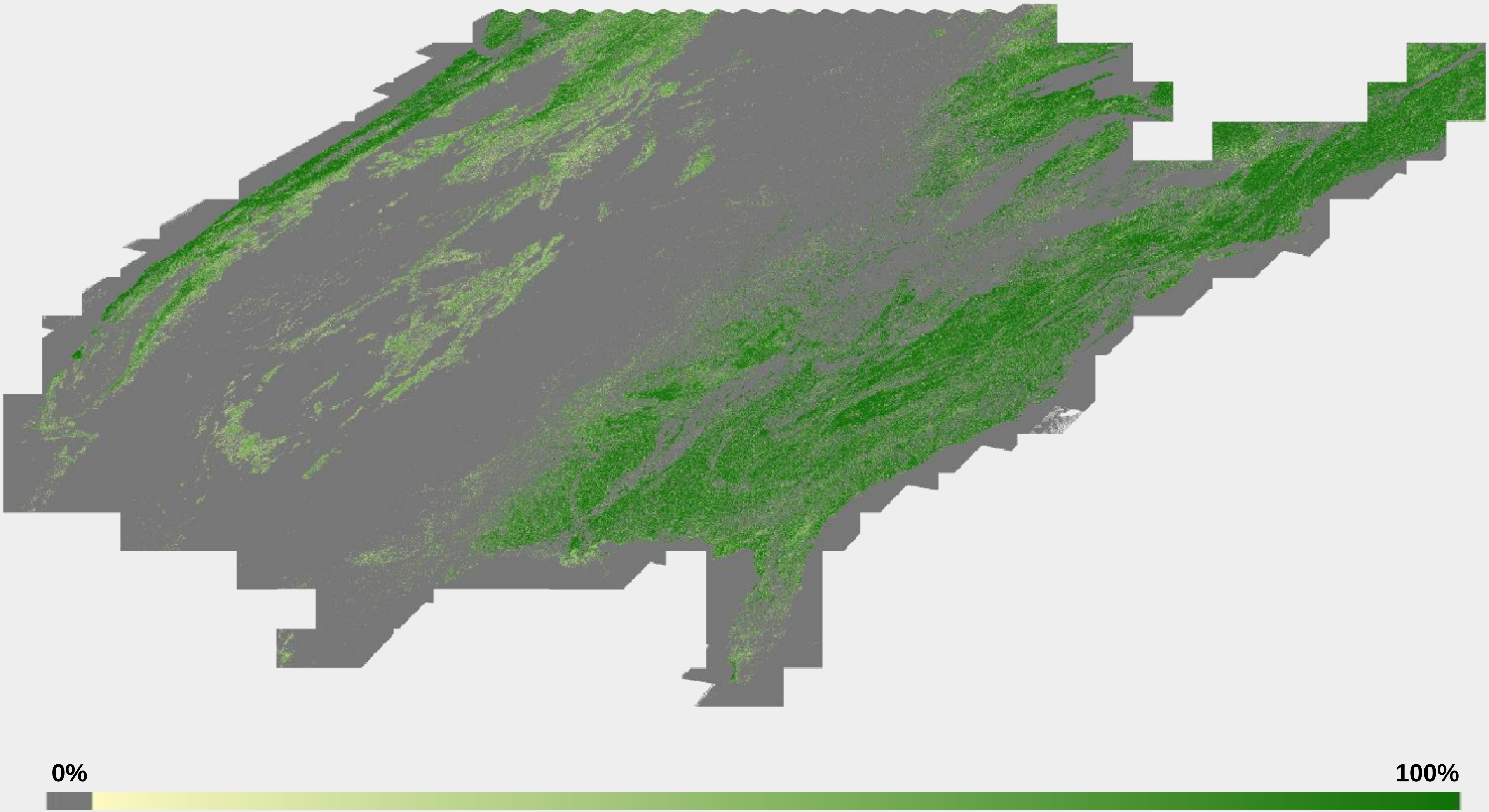


30 metrics (percentiles 10, 25, 50, 75 and 90) derived from 30m Landsat 5 and 7 bands 1, 2, 3, 4, 5, 7 from 5 years (2008-2012) time period were used as explanatory variables.

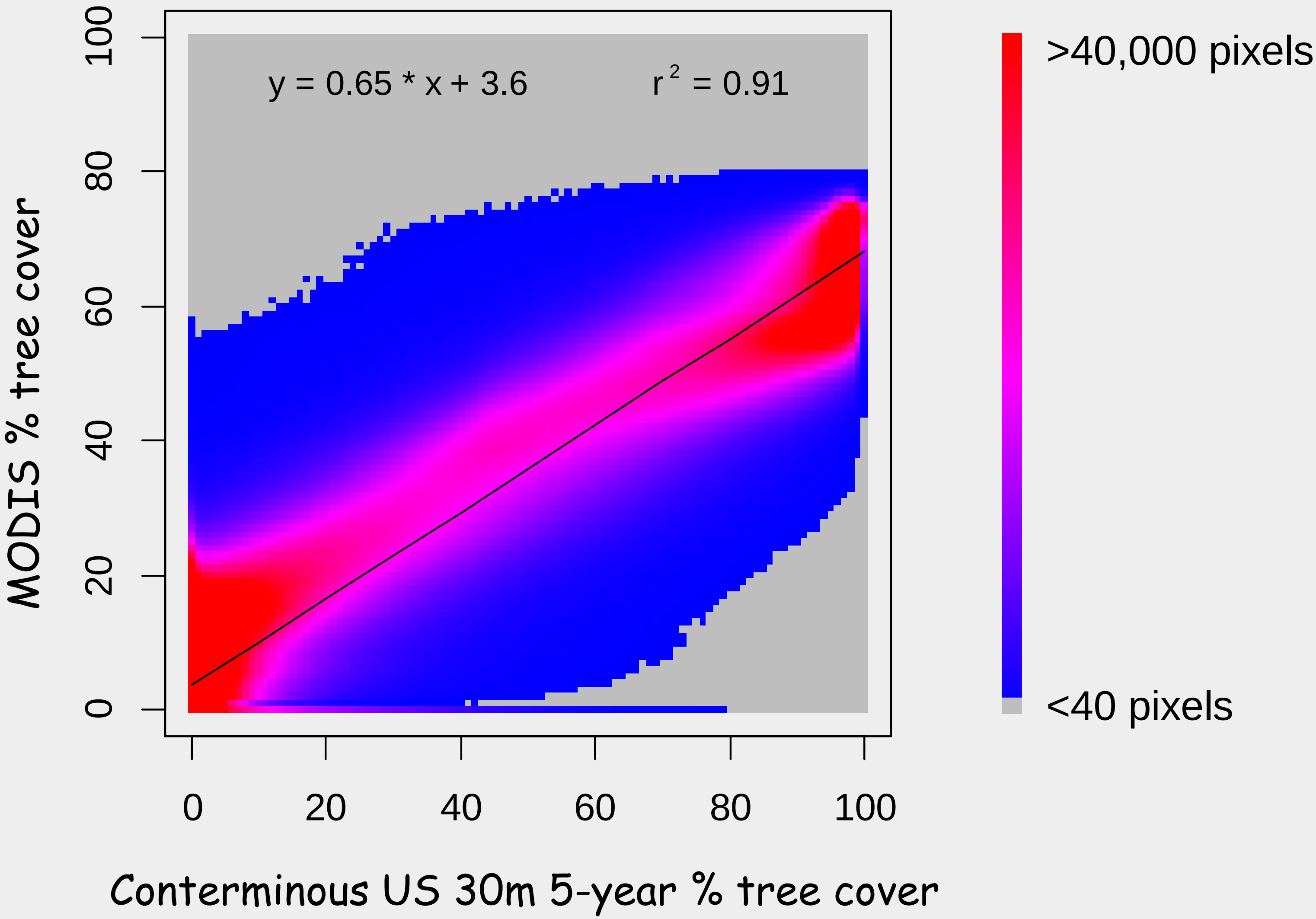
Conterminous US 30m 5-year % tree cover product generation



Conterminous US 30m 5-year (2008-2012) % tree cover final product



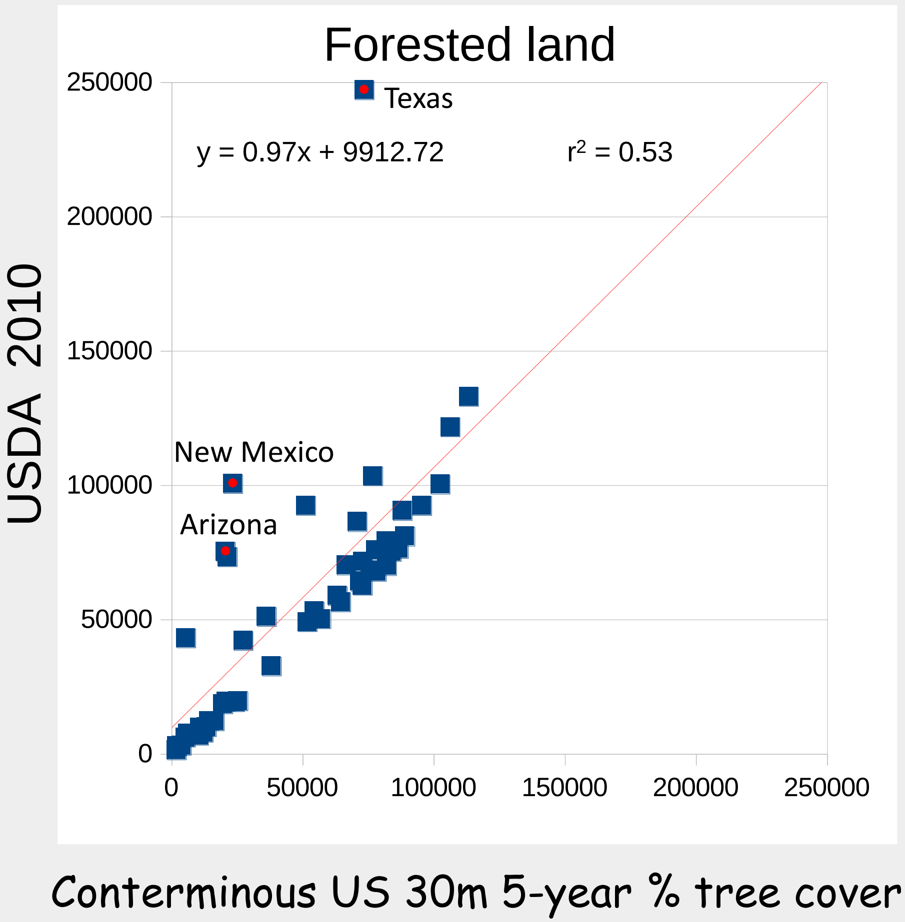
Conterminous US 30m 5-year % tree cover
vs
median MODIS 2008-2012 250m % tree cover (MOD44B)

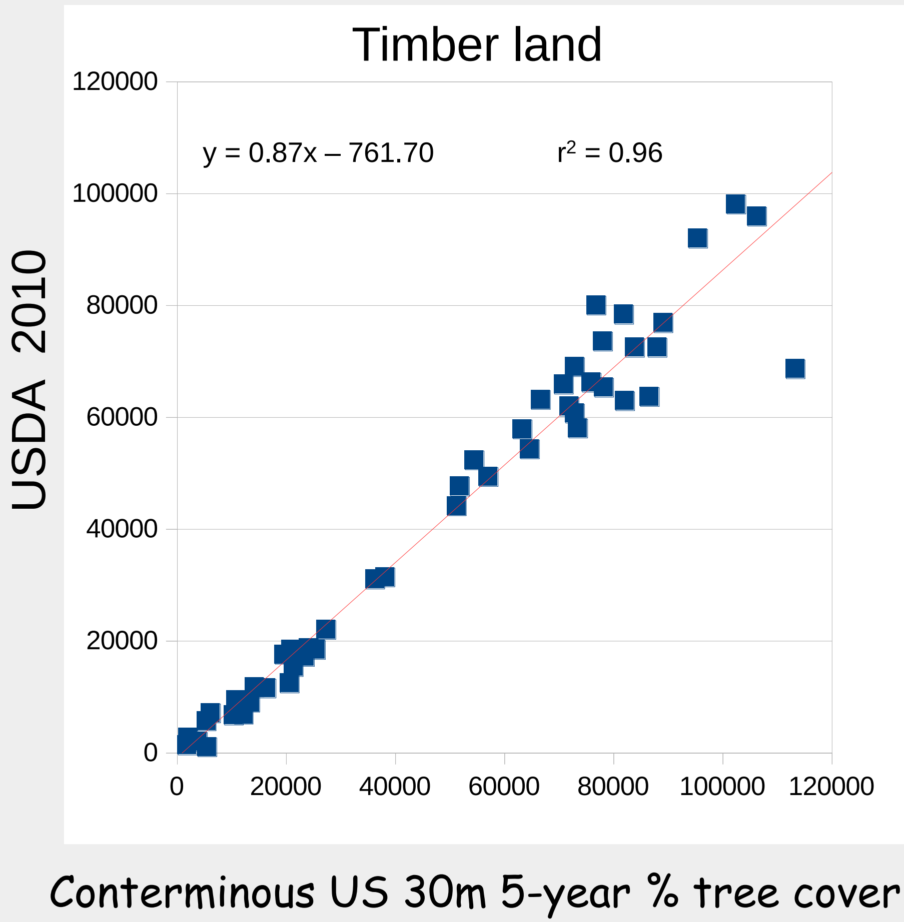


State by state comparison with USDA census 2010, km^2

http://apps.fs.fed.us/fiadb-downloads/FIADB6_pop_estimates.html

Census: Nevada - 2012, New Mexico – 2013, Washington – 2011, Wyoming – 2012, all other states – 2010.





- States Texas, New Mexico and Arizona include Juniper bush lower than 5 m in forest land

Summary

We present a new classification approach, based on:

- Active learning technique, adapted to remote sensing data processing
- New feature space partitioning algorithm
- Targeted sampling as substitution of random sampling

Advantages of the approach:

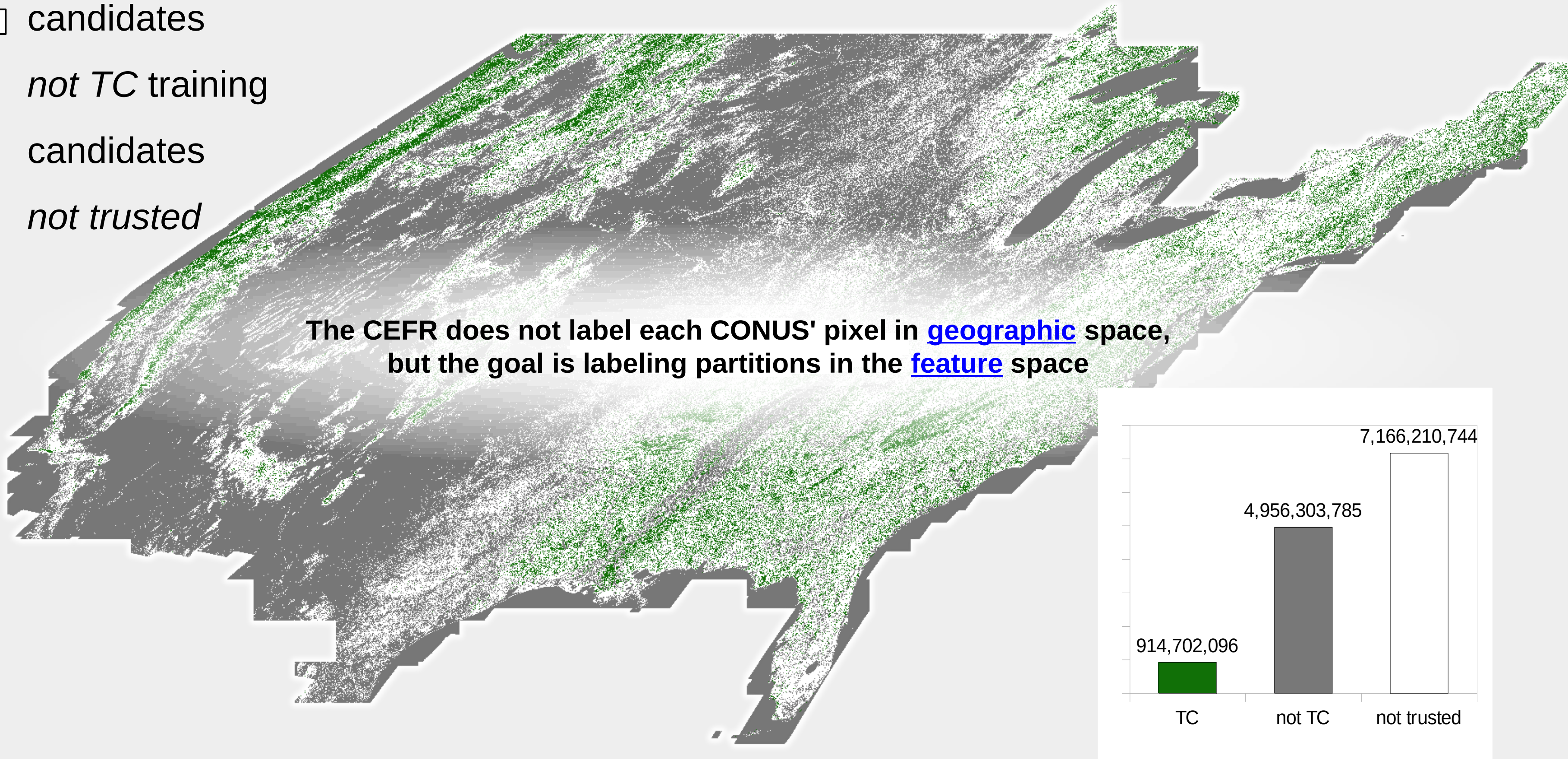
- Compact and representative training (including rare variations)
- Computationally efficient, applicable to continental and global scale projects
- Minimize cost of obtaining labeled data

References

- Egorov A.V., Hansen, M.C., Roy, D.P., Kommareddy, A., Potapov, P.V., 2015, Image interpretation-guided supervised classification using nested segmentation, *Remote Sensing of Environment,* 165, 135–147
- Hansen, M.C., Egorov, A, Roy, D.P., Potapov, P., Ju, J., Turubanova, S., Kommareddy, I., Loveland, T. , 2011, Continuous fields of land cover for the conterminous United States using Landsat data: First results from the Web-Enabled Landsat Data (WELD) project. *Remote Sensing Letters*, 2, 4:279-288.
- Hansen, M.C., Egorov, A., Potapov, P.V., Stehman, S.V., Tyukavina, A., Turubanova, S.A., Roy, D.P., Goetz, S.J., Loveland, T.R., Ju, J., Kommareddy, A., Kovalskyy, V., Forsythe, C., Bents, T., 2014, Monitoring conterminous United States (CONUS) land cover change with Web-Enabled Landsat Data (WELD), *Remote sensing of Environment*, 140, 466-484

2-class commission error-free reference (CEFR) data generation

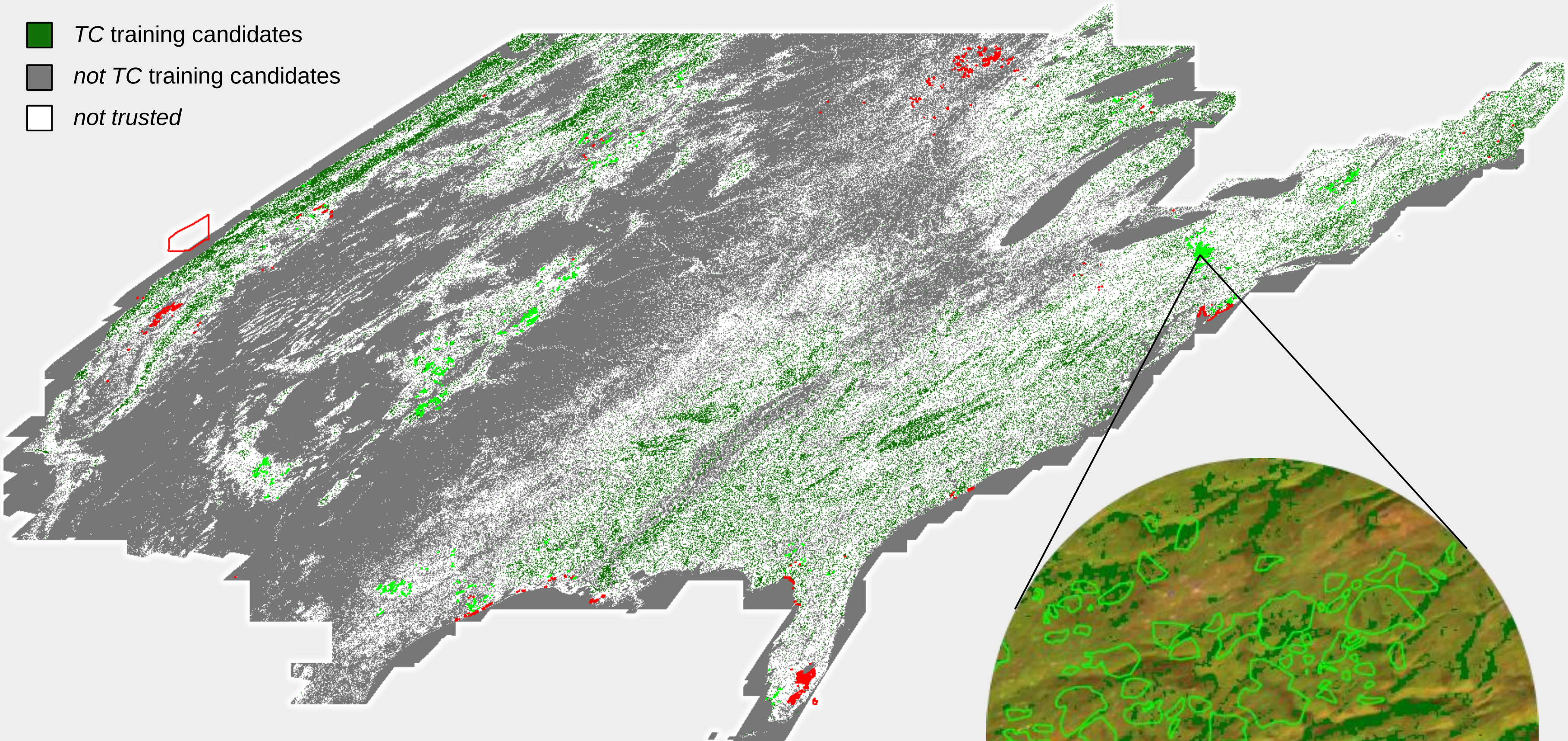
- *TC* training candidates
- *not TC* training candidates
- *not trusted*



The CEFR does not label each CONUS' pixel in [geographic]() space, but the goal is labeling partitions in the [feature]() space

- *TC* training candidates (7% of CONUS' pixels) include areas, sustainable classified as forest in all classifications over 10 years (2003-2012).
- *Not TC* training candidates (38% of CONUS' pixels) were never classified as forest over 10 years.
- 55% of CONUS' pixels are flagged as *not trusted*.

Filling gaps in CEFR



Manually digitized polygons fill gaps in CEFR

28,543 polygons (3,237,658 pixels) of *TC* class
11,826 polygons (19,251,074 pixels) of *not TC* class

That adds 0.38% of training candidates, already existing in CEFR